

# Application of Information Theory, Lecture 5

## Channel Capacity and Isoperimetric Inequality

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# Part I

## Channel Capacity

## The problem

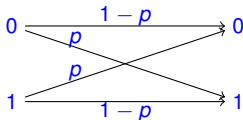
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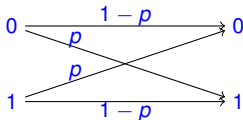
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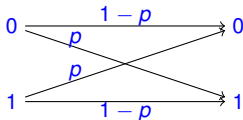
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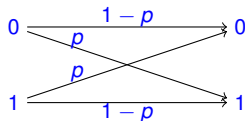
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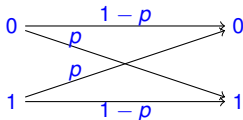


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- ▶ Can we send bits with smaller error?

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- ▶ Before Shannon it was believed that very small error rate requires very small transmission rate.

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- ▶  $C_p$  might be 0 (i.e., for  $p = \frac{1}{2}$ )
- ▶ A revolution in EE and the whole world

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## Theorem 1

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- ▶ Tight theorem
- ▶ We prove a weaker variant that holds w.h.p. over  $\mathbf{x} \leftarrow \{0, 1\}^m$

# Hamming distance

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- ▶ For  $\mathbf{y} = (y_1, \dots, y_n) \in \{0, 1\}^n$ , let  $\|\mathbf{y}\|_1 = \sum_i y_i$  — Hamming weight of  $\mathbf{y}$

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- ▶ We sometimes just write  $|\mathbf{y}|$ .



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- ▶ We show  $\exists f: \{0, 1\}^m \mapsto \{0, 1\}^n$  and  $g: \{0, 1\}^n \mapsto \{0, 1\}^m$ , s.t.  
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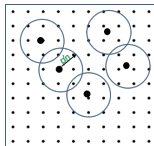
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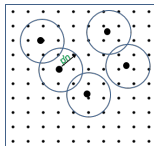
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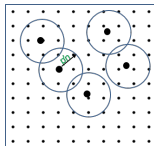
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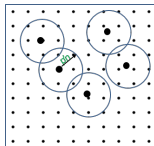
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# Proving there exists good $f$

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# Tightness



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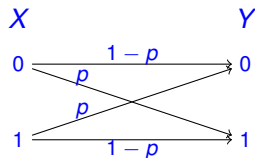
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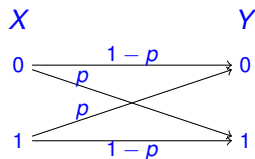
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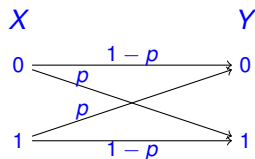
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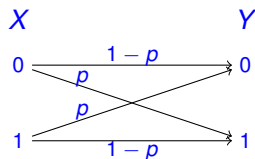


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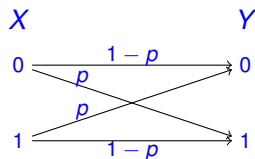
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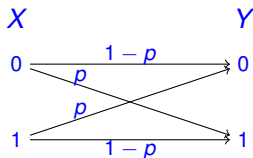
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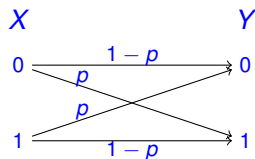
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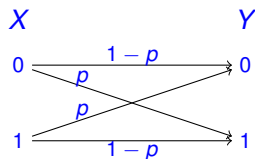
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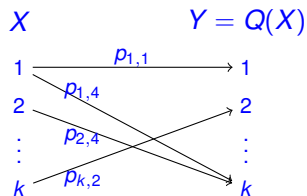
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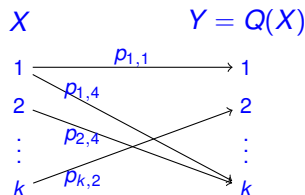


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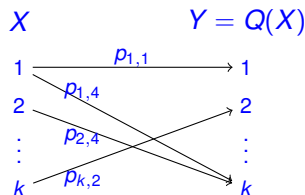


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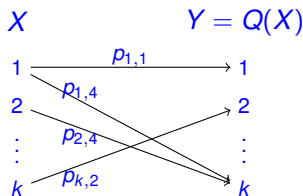


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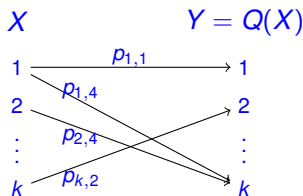


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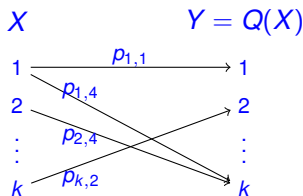


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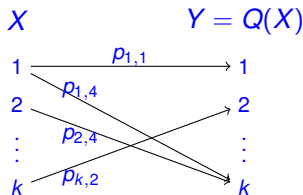


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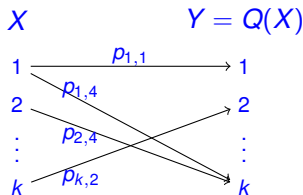


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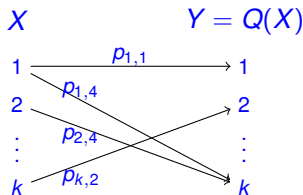


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- ▶ Shannon theorem:  $\forall Q$  and  $\forall \varepsilon > 0$ ,  $\exists m_\varepsilon: \forall m > m_\varepsilon$  and  $\forall n > m(\frac{1}{C_Q} + \varepsilon): \exists f, g$  as above s.t.  $\Pr_Q[g(Q(f(\mathbf{x}))) \neq \mathbf{x}] \leq \varepsilon$ , for all  $\mathbf{x} \in \{0, 1\}^m$ .



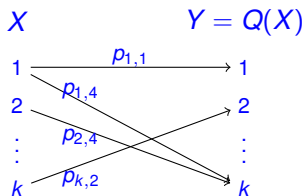
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# Part II

## Hamming Ball

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## Corollary 3

For  $y \in \{0, 1\}^n$  and  $p \in [0, \frac{1}{2}]$ , let  $B_p(y) = \{y' \in \{0, 1\}^n : \|y' - y\|_1 \leq pn\}$ .

Then  $|B_p(y)| = \sum_{k=0}^{\lfloor pn \rfloor} \binom{n}{k} \leq 2^{n \cdot h(p)}$

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- ▶  $\sum_i X_i \leq pn \implies \mathbb{E}[\sum X_i] \leq pn$ , and by symmetry  $\mathbb{E}[X_i] \leq p$  for every  $i$
- ▶ Hence,  $\Pr[X_i = 1] \leq p$  for every  $i$ .

$\implies H(X_i) \leq h(p)$  for every  $i$

$\implies |\mathcal{S}| \leq 2^{\sum_i H(X_i)} \leq 2^{nh(p)}$

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## Corollary 3

For  $y \in \{0, 1\}^n$  and  $p \in [0, \frac{1}{2}]$ , let  $B_p(y) = \{y' \in \{0, 1\}^n : \|y' - y\|_1 \leq pn\}$ .  
Then  $|B_p(y)| = \sum_{k=0}^{\lfloor pn \rfloor} \binom{n}{k} \leq 2^{n \cdot h(p)}$

Very useful estimation. Weaker variants follows by AEP or Stirling,

## Hamming ball, cont.

The above bound yields the following concentration bound:

### Corollary 4

Let  $X_1, \dots, X_n$  be iid uniform bits and let  $p \in [0, \frac{1}{2}]$ , then  
 $\Pr [\sum_i X_i \leq pn] = \Pr [(X_1, \dots, X_n) \in \mathcal{S}] \leq 2^{nh(p)} \cdot 2^{-n} = 2^{-n(1-h(p))}.$

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Very useful inequality. No Chernoff just IT

# Part III

## **Combinatorial Applications**

# Movies

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- ▶ Hence,  $X$  is not determined by  $Y$

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- ▶ Equality if  $\mathcal{S}$  is “face” :  $\mathcal{S} = \{(\mathbf{x}, \mathbf{y}) : \mathbf{y} \in \{0, 1\}^d\}$  for some  $\mathbf{x} \in \{0, 1\}^{n-d}$
- ▶ Example:  $\mathcal{S}$  is a **face** of the 3-dimensional cube  
 $n = 3, |\mathcal{S}| = 4$ , implies  $|E| \leq \frac{1}{2} \cdot 4 \cdot \log 4 = 4$
- ▶  $E_i$  — edges of  $E$  in **direction**  $i$  ( $E = \bigcup_{i \in [n]} E_i$ )
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## Lemma 6

$$H(X_i | X_{-i}) = \frac{2|E_i|}{|\mathcal{S}|}$$

Proving **Thm 5**:

$$\begin{aligned} \log |\mathcal{S}| = H(X_1, \dots, X_n) &= H(X_1) + H(X_2 | X_1) + \dots + H(X_n | X_1, X_2, \dots, X_{n-1}) \\ &\geq H(X_1 | X_{-1}) + H(X_2 | X_{-2}) + \dots + H(X_n | X_{-n}) = \sum \frac{2|E_i|}{|\mathcal{S}|} = \frac{2|E|}{|\mathcal{S}|} \end{aligned}$$

# Isoperimetric inequality

- ▶  $\mathcal{S} \subseteq \{0, 1\}^n$
- ▶ Edges of  $\mathcal{S}$  —  $E = \{(u, v) \in \mathcal{S} : |u - v| = 1\}$

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